



A Generalized Deep Neural Network for Estimating Severe Hail Likelihood from Satellite Infrared Cloud Top Patterns and Microwave Radiances

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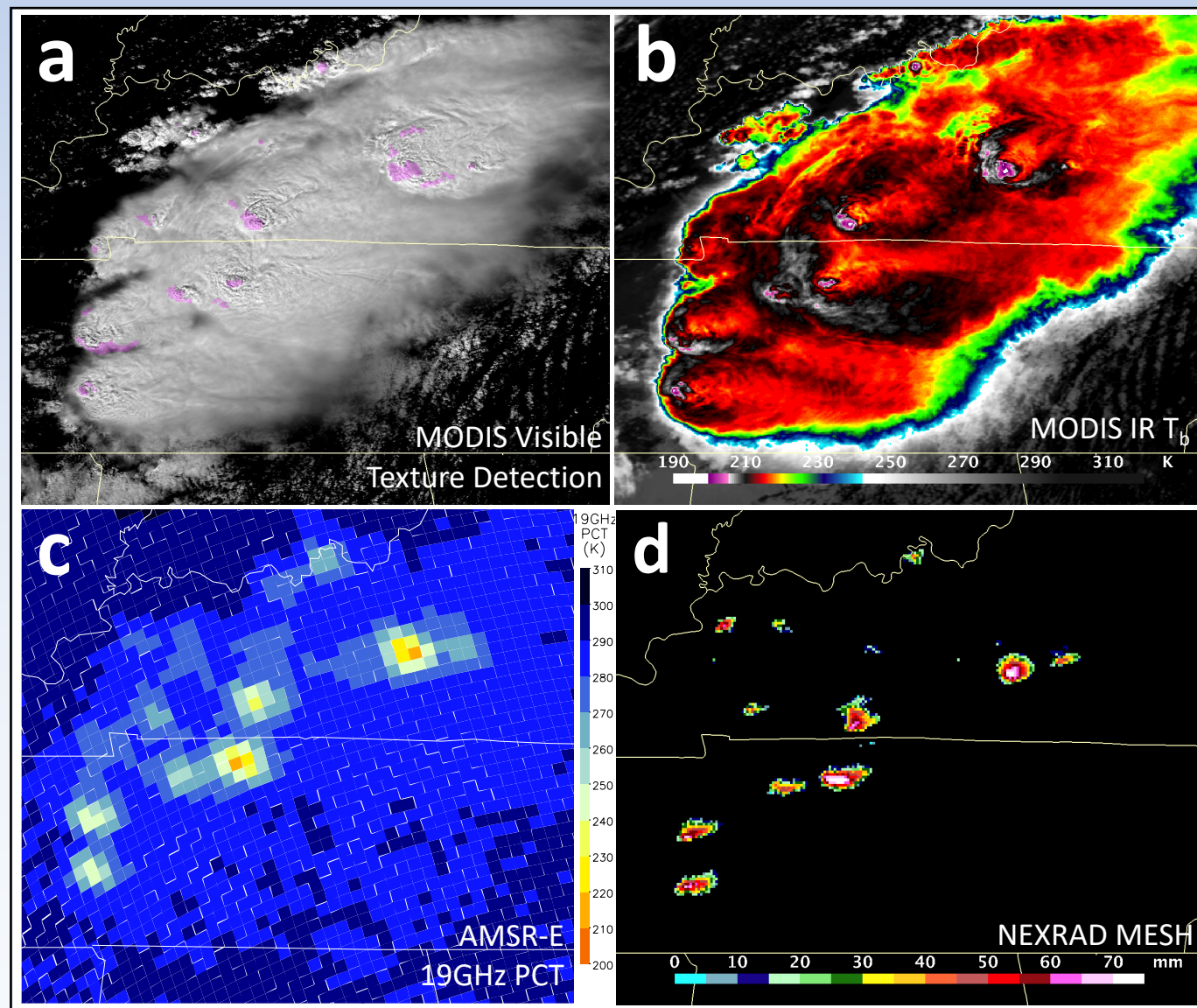
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Background

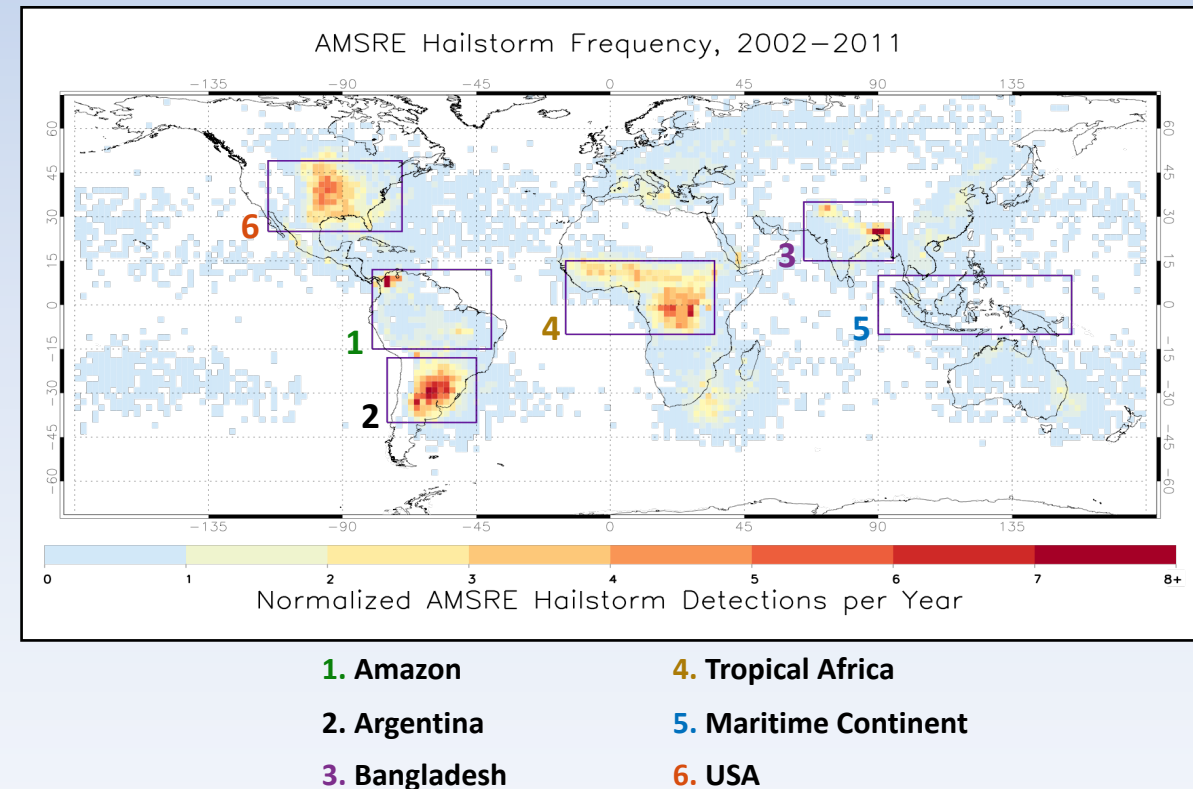
- Satellite visible/infrared (IR) imager and microwave radiometer (MWR) signatures of severe weather
 - Highly textured imagery
 - Cold cores < 200 K,
 - Strong 19-GHz PCT depression signifying strong scattering
- NEXRAD measurements of Maximum Expected Size of Hail (MESH) for ground truth
 - More consistent than human spotters and storm reports
 - USA only

Novel demonstration of how combined satellite IR, MWR, and atmospheric reanalysis data can estimate severe hail likelihood with relatively high accuracy



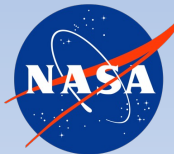
Severe-weather outbreak over Kentucky and Tennessee, 7 April 2006

- All Aqua orbits coincident with MESH captured using the Langley Automated Sensor Inter-calibration System (LASICS)
 - Satellite *science opportunity* identification tool
 - Local 01:30/13:30 not strongly favorable to hail over USA
- Deep neural network (DNN) trained to map MODIS (IR), AMSR-E (MWR), and/or MERRA-2 reanalysis predictors to MESH over the USA
 - 1,949 samples split 60%, 20%, and 20% across training, validation, and testing sets
 - 6-fold cross-validation
 - Estimates likelihood of 95th percentile MESH > 1.5"
 - True / Null = 48% / 52%
- Evaluate predictor importance using *Recursive Feature Elimination*
- Explore variable space as a function of hail likelihood globally

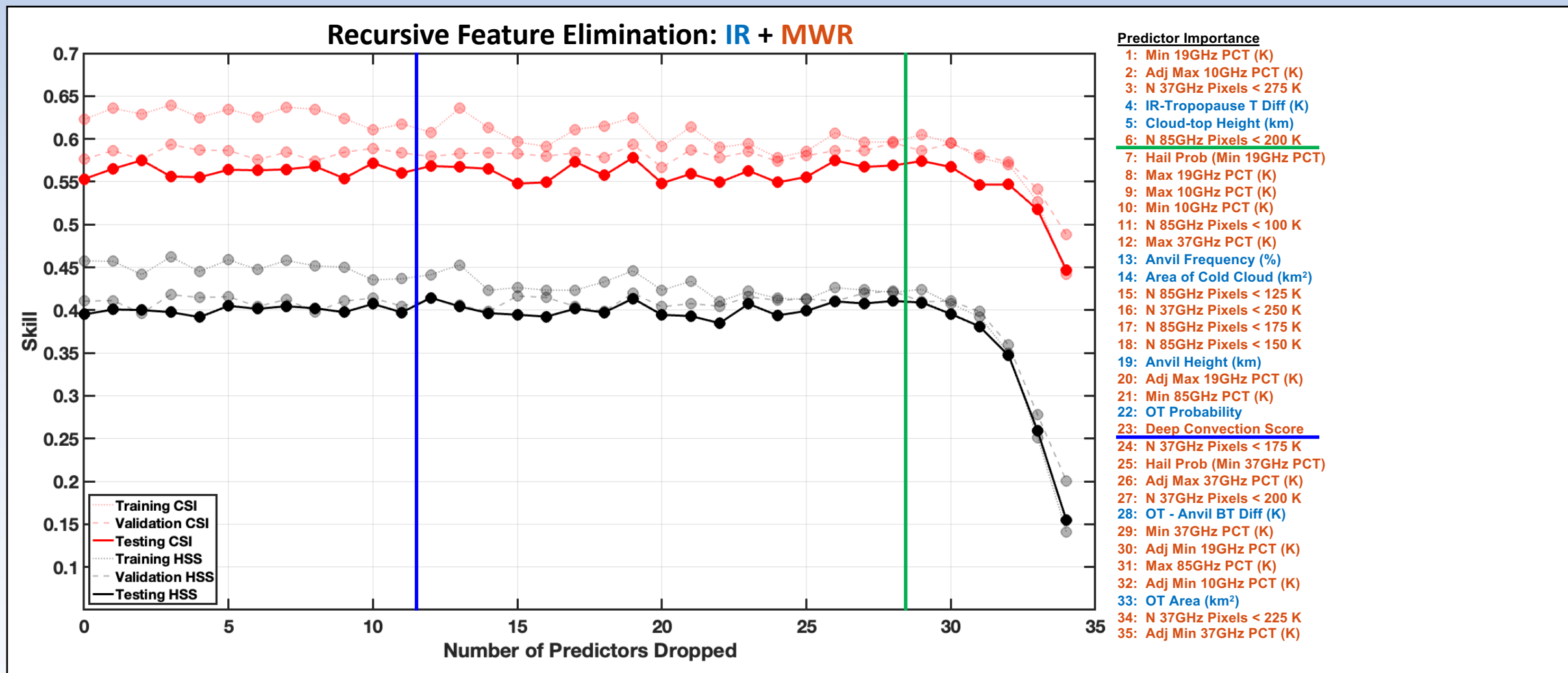


Questions:

1. How skillfully can a DNN estimate severe hail likelihood?
2. How do IR, MWR, and MERRA-2 reanalysis predictors contribute to that skill?
3. Is the model globally generalized – how do predictors vary across distinct regions?



Neural Network Predictor Importance

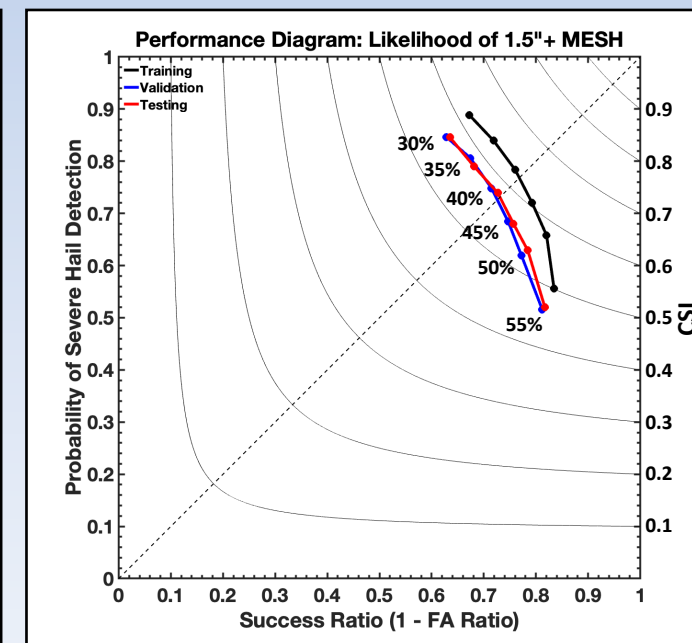
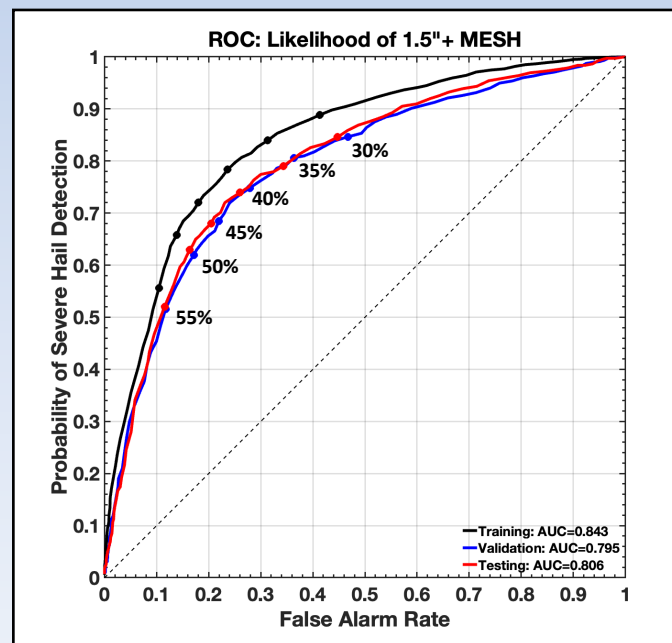
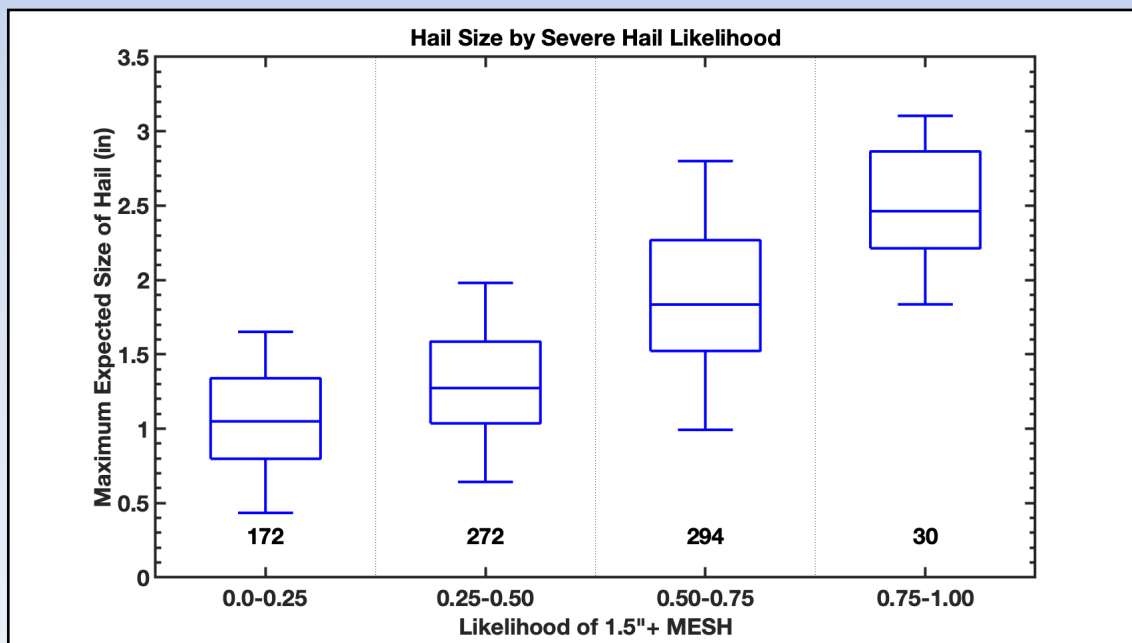


- Train model with all predictors
- Exclude one feature and retrain
- Eliminate least contributing feature and repeat

19 GHz PCT is a strong, unique signal that's very sensitive to ice scattering

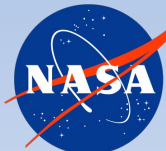


Neural Network Skill: IR + MWR Predictors

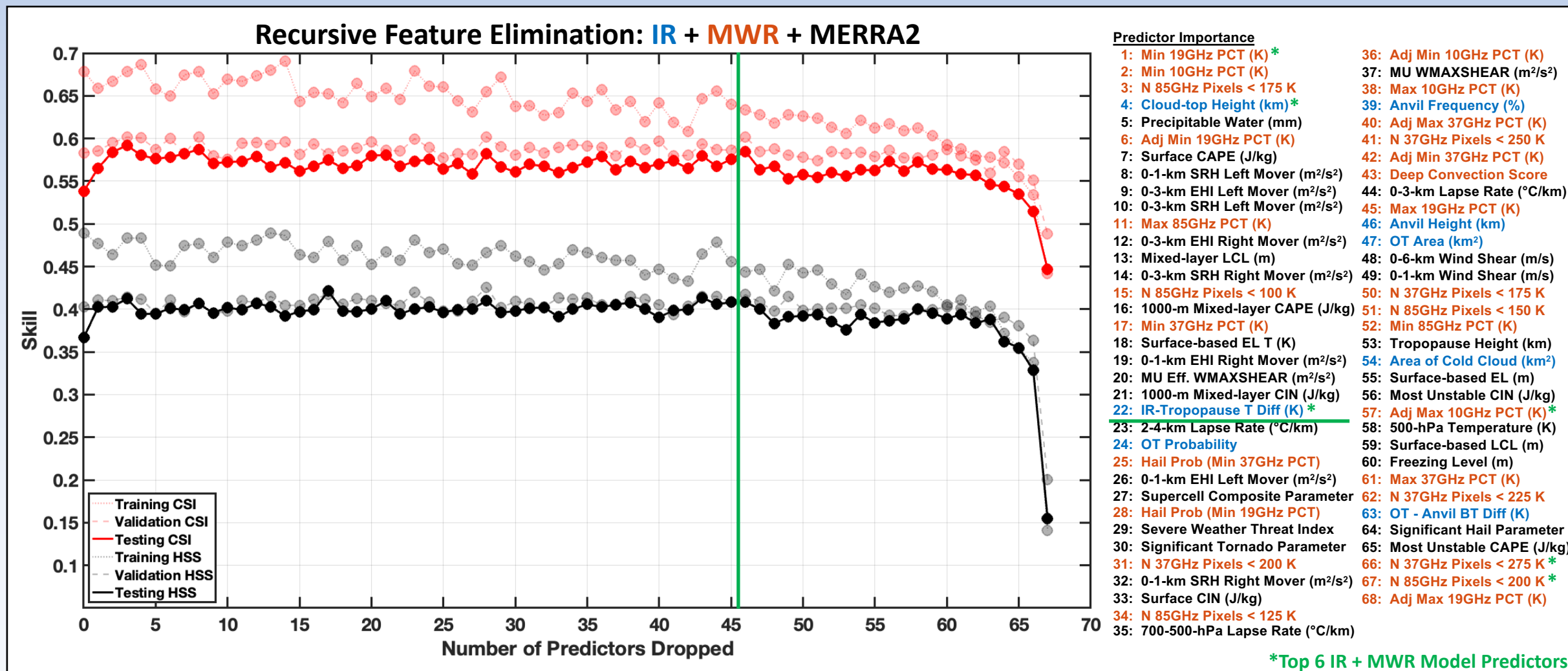


DNN is assigning the highest likelihoods to storms with the greatest MESH

- High fold variance and overfitting perhaps owed to low sample size
- Generalization possible with reasonable skill
- 6-fold Testing set skill exceeds 0.41 (± 0.03) HSS and 0.56 (± 0.02) CSI at ~50/50 class split
 - 70% ($\pm 5\%$) Recall, 76% ($\pm 6\%$) Precision, 20% ($\pm 7\%$) False Alarm Rate
 - Suggests *balanced* performance



Neural Network Predictor Importance

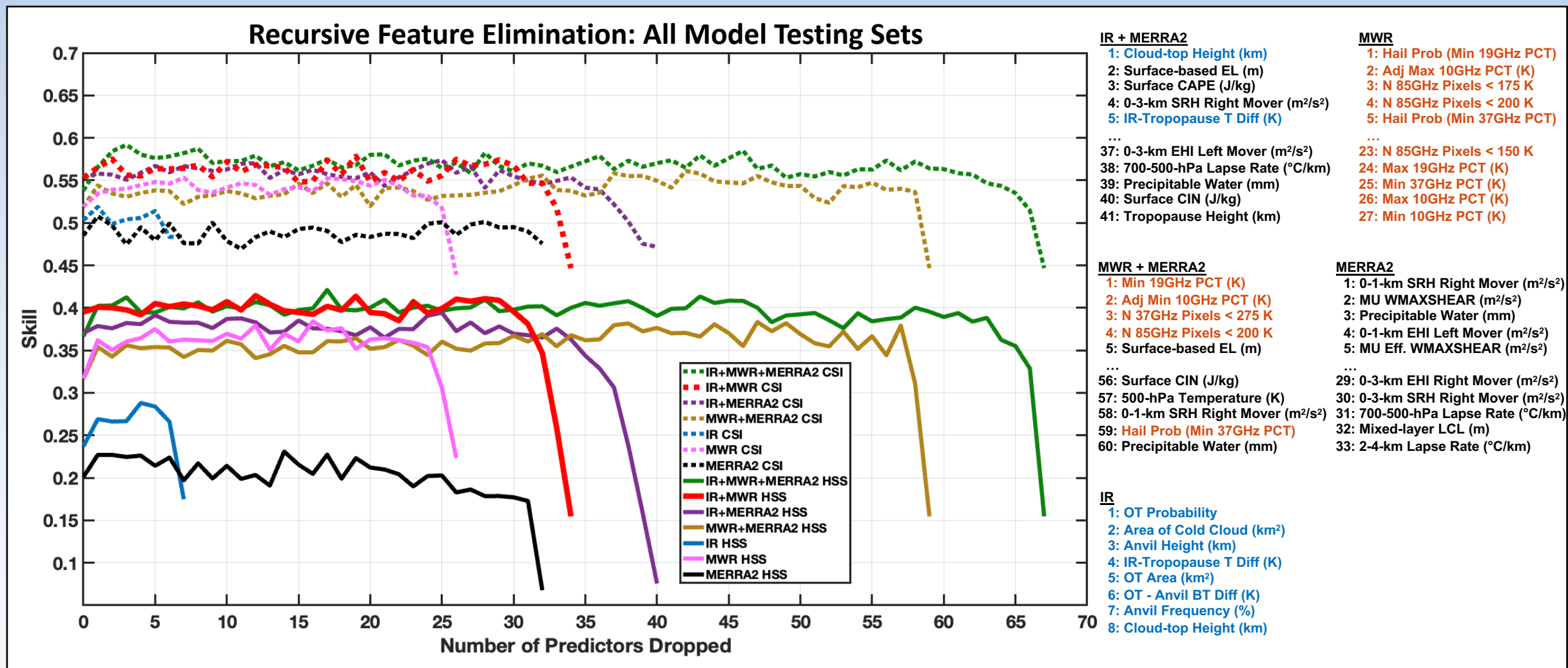


- A feature may be deemed “unimportant” because of irrelevancy or redundancy
- That is, information may be important, but is already contained in remaining features

Significantly correlated features
may “demote” one another



Neural Network Predictor Importance

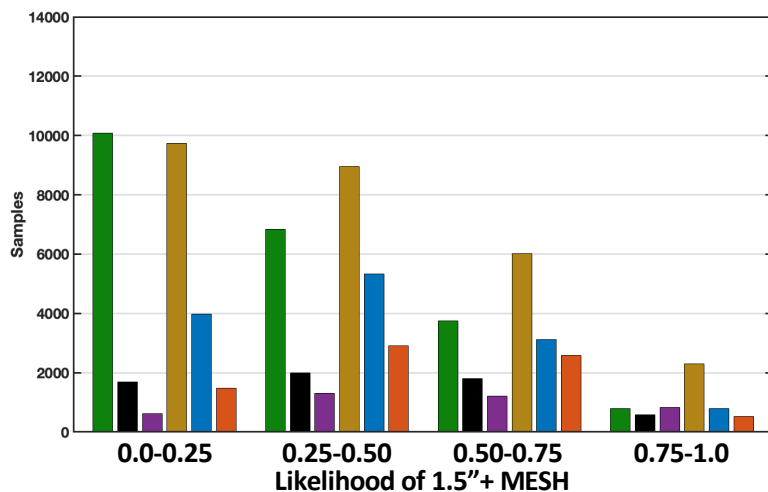


- IR+MWR model shows similar features sensitivity and skill to that of the IR+MWR+MERRA-2 model
- IR- or MERRA-2-only models have poorest skill
- Min 19-GHz PCT remains consistently important

**A DNN with MWR predictors
alone is the most capable
single-source model**

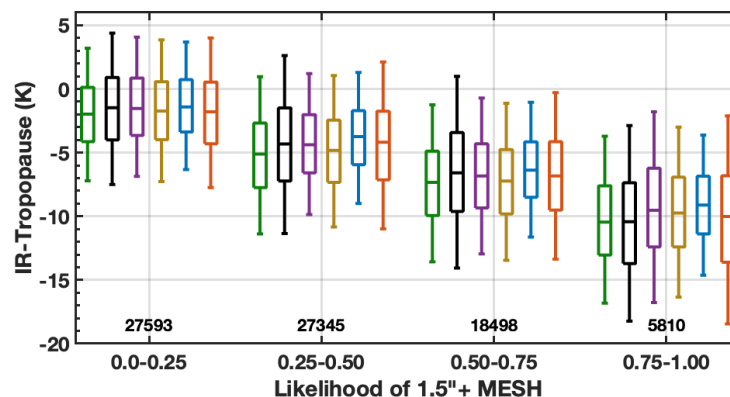


Variable Space by Region

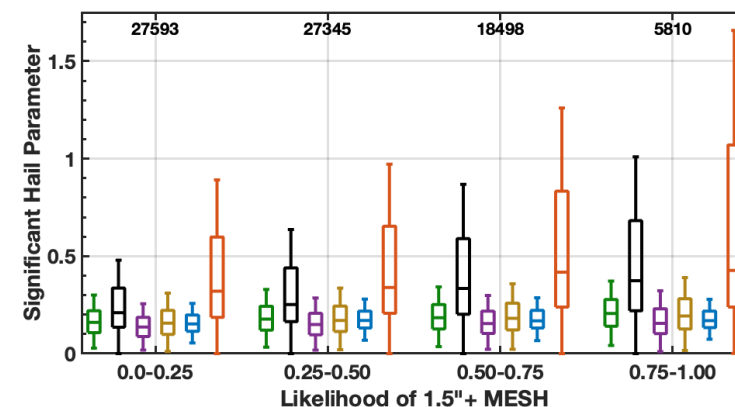
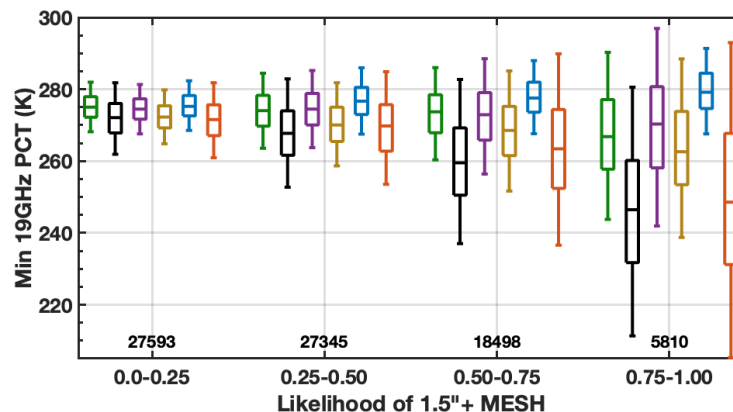
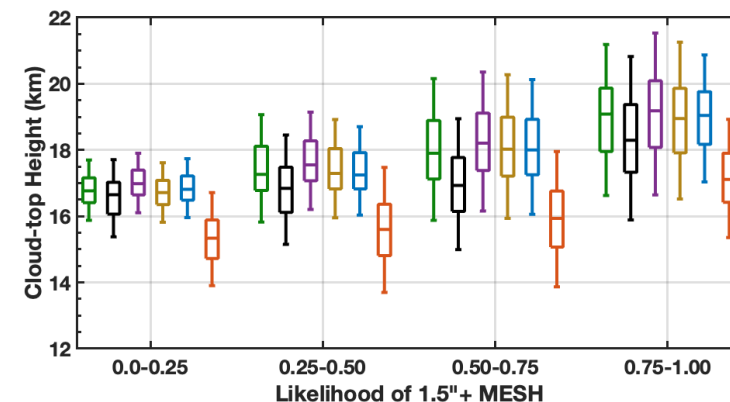


Training a model over USA with MERRA-2 is going to reinforce MERRA-2 – also cloud heights and cold area

By IR + MWR Model Likelihoods



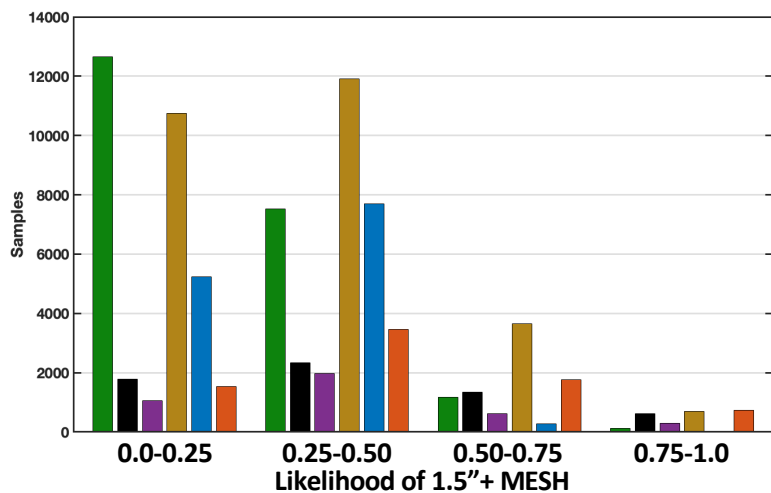
Amazon Argentina Bangladesh Tropical Africa Maritime Continent USA



- Are predictor variables well grouped?
- Height and environment not generalized predictors
- Maritime Continent has peculiarly high likelihoods



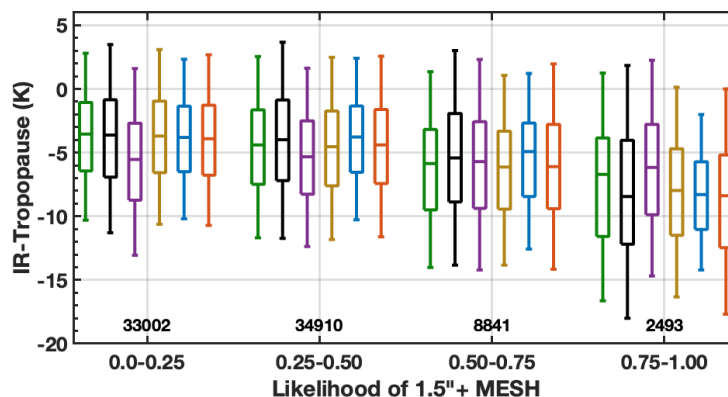
Variable Space by Region



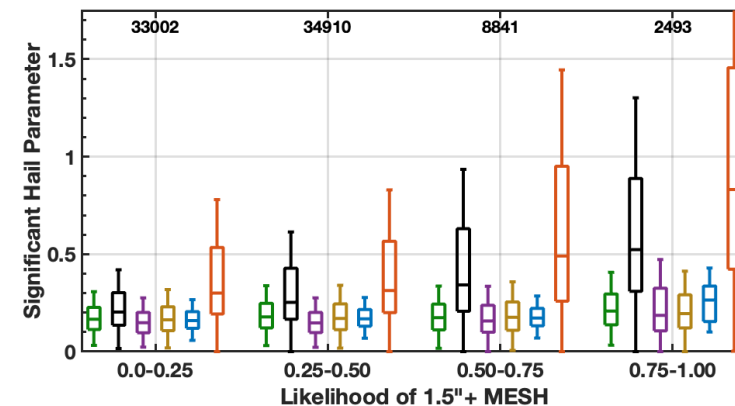
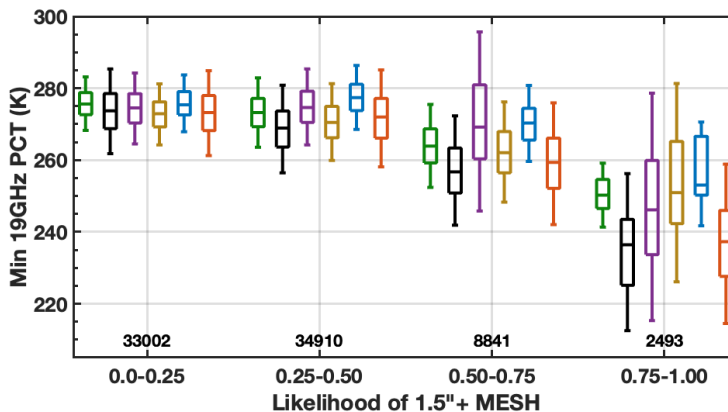
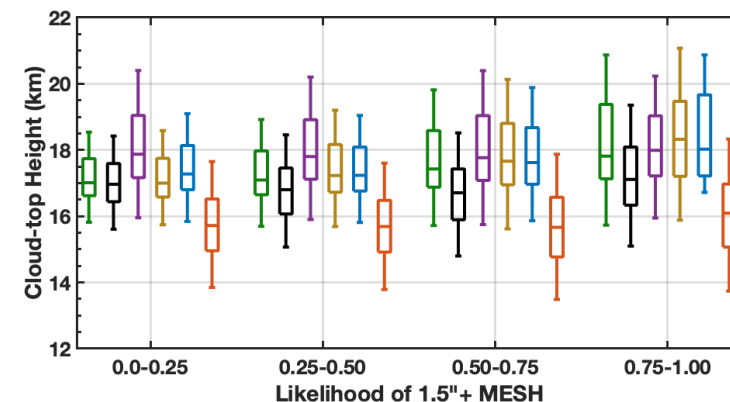
Larger features are preferred when model is trained on MWR – dominates otherwise strong IR patterns

- Better grouping of MWR
- IR-Trop signal is downplayed

By MWR Model Likelihoods



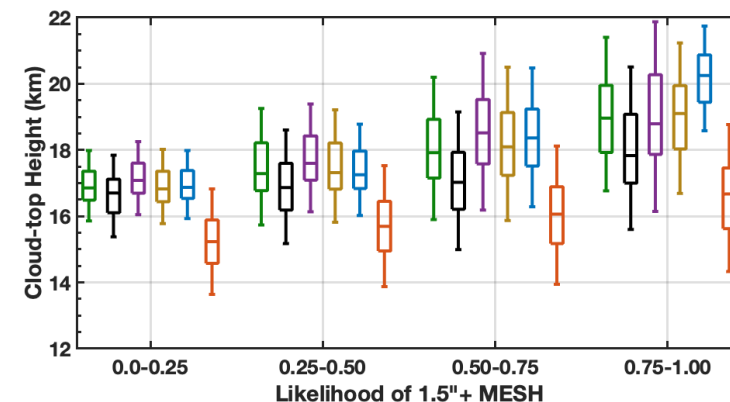
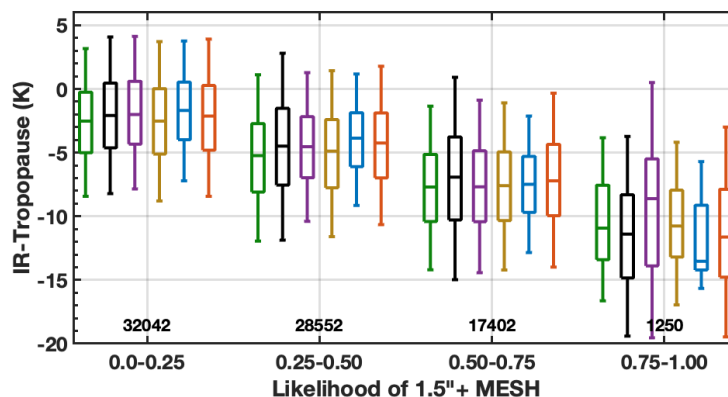
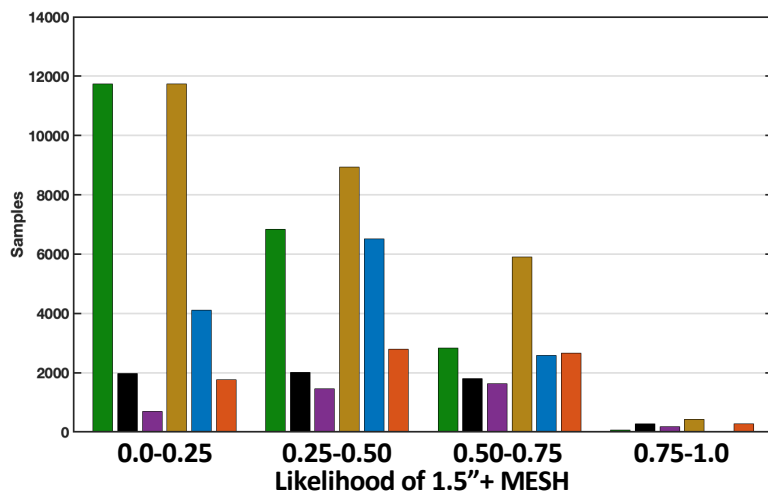
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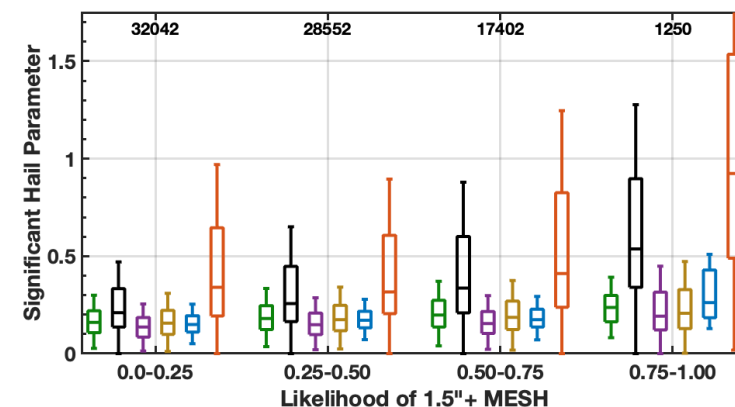
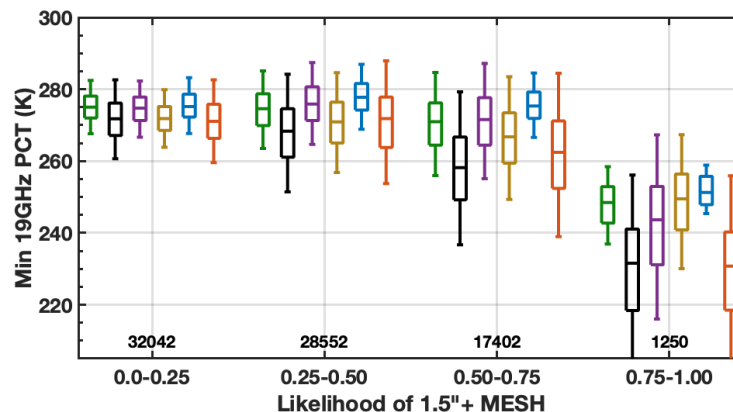
Variable Space by Region

By Alternative IR + MWR Model Likelihoods (no heights, cold cloud area, or 37-GHz PCT)



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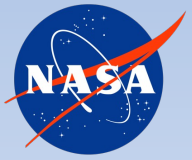
Removing latitude-dependent variables helps improve generalization – but constrains predictive dynamics range



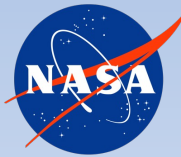
- Sample size limitations hurting skill of more generalized model
- Poorly generalized predictors can be specifically important – not a lot of sample size to work with if losing key predictors

Key Predictors		
Thermodynamic	Kinematic	Scale
IR-Tropopause T Diff (K)	Storm Relative Helicity (m^2/s^2)	19GHz PCT (K)
Surface-based EL (m)	Energy Helicity Index (m^2/s^2)	10GHz PCT (K)
Surface-based CAPE (J/kg)	WMAXSHEAR (m^2/s^2)	N 85GHz Pixels
Precipitable Water (mm)		Area of Cold Cloud (km^2)

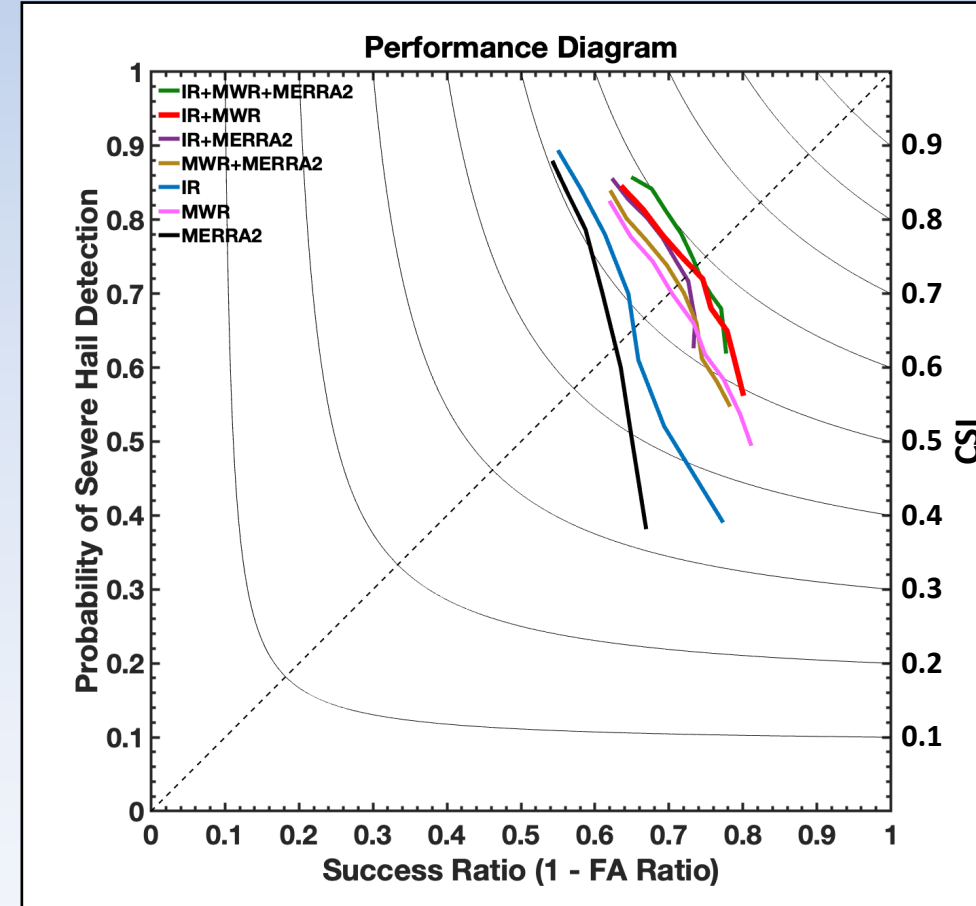
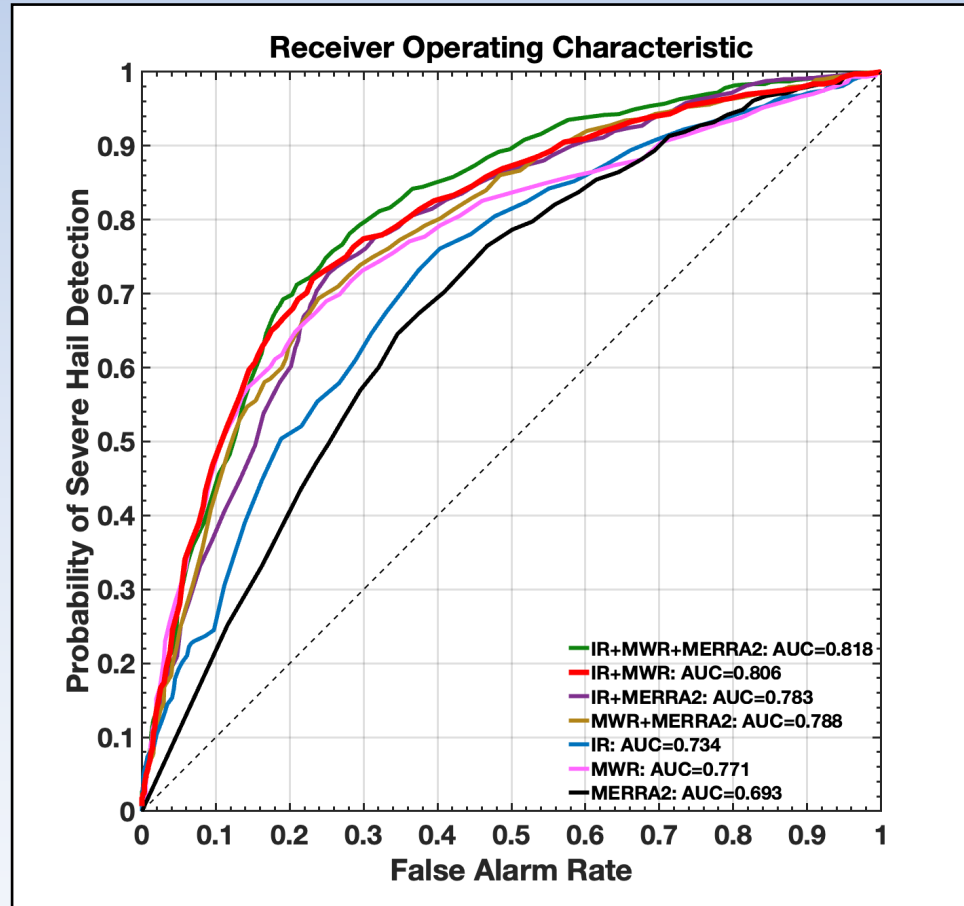
- IR+MWR DNN skillfully estimates severe hail likelihood
- MERRA-2 reanalysis predictors offer slightly better skill, but are less globally generalized
- Larger features are preferred when model is trained on MWR – which is also more latitudinally-independent than models that include IR in training



Additional Slides

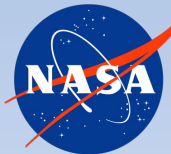


Neural Network Skill: All Model Testing Sets



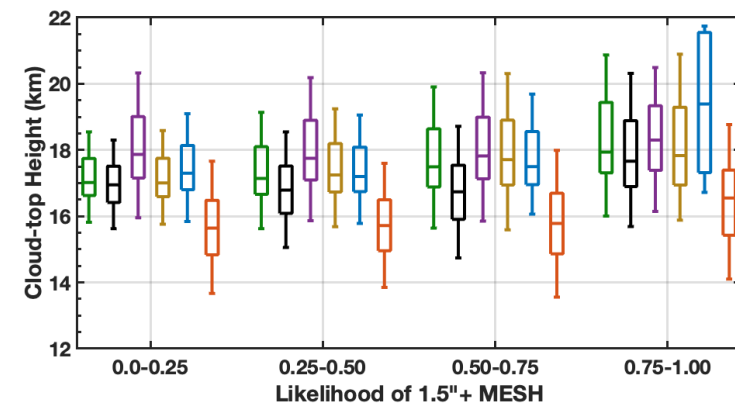
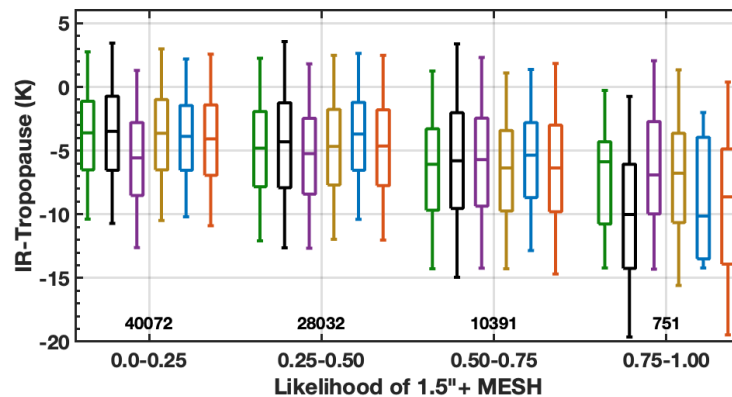
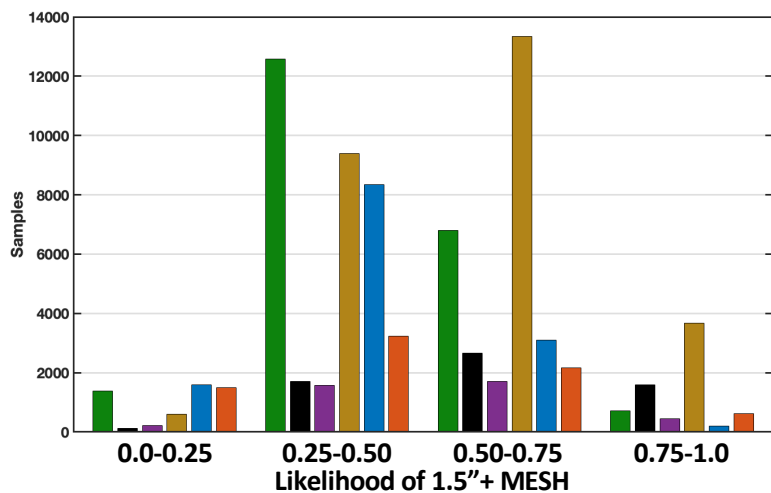
- Model most skillful when combining all IR + MWR satellite observations and MERRA-2
- IR + MWR combination model remains reasonably skillful

**Important to consider
regionally dependency or
atmospheric environment**

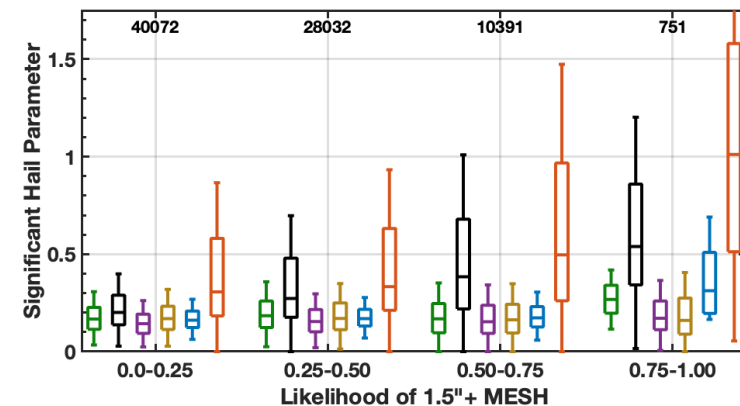
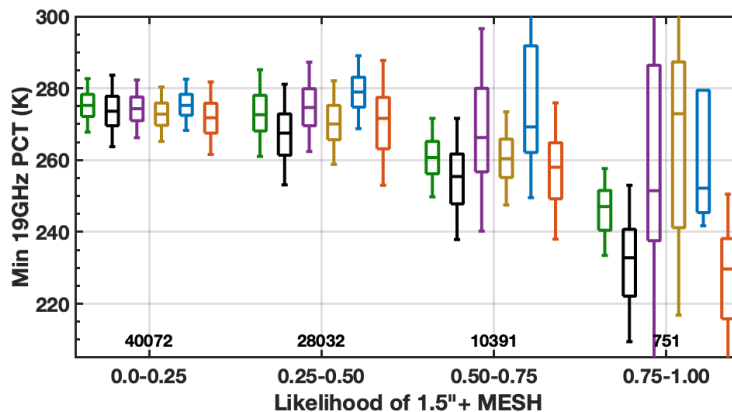


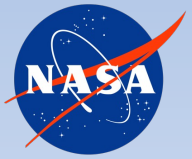
Variable Space by Region

By IR + MWR + MERRA2 Model Likelihoods

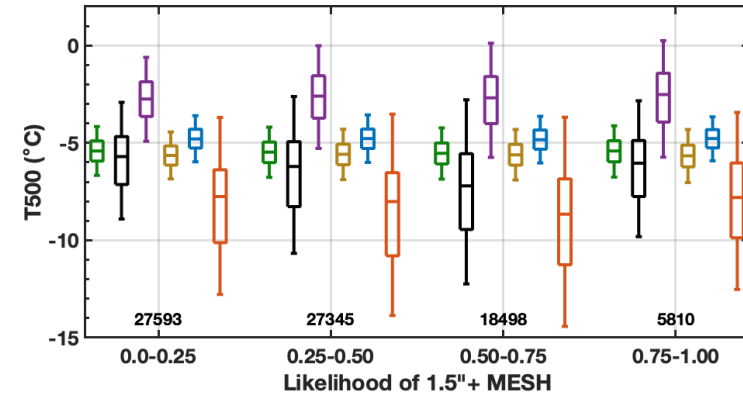
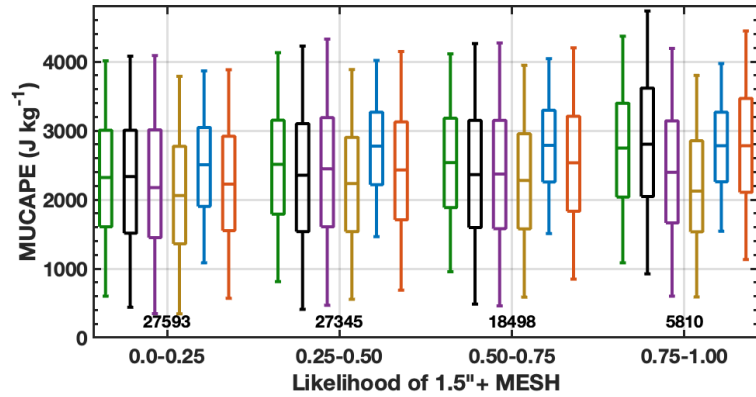


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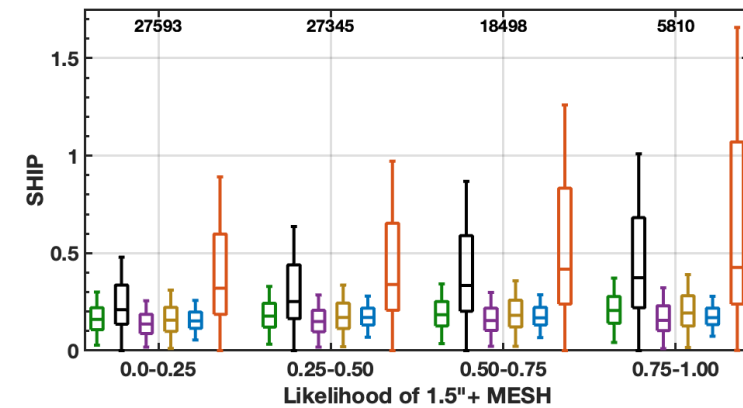
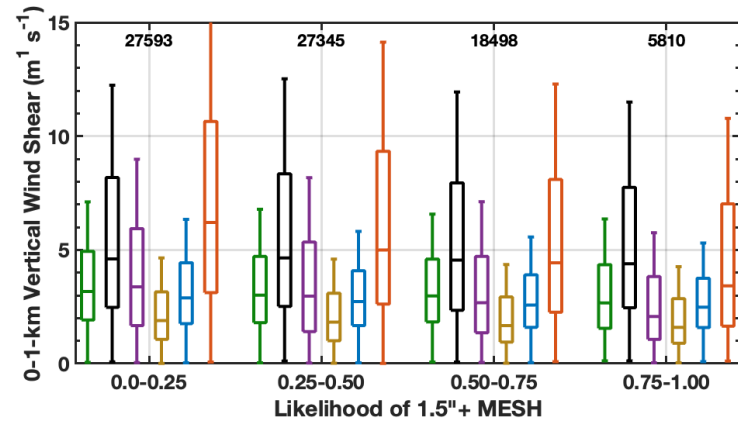




Additional Satellite MERRA2 by Region

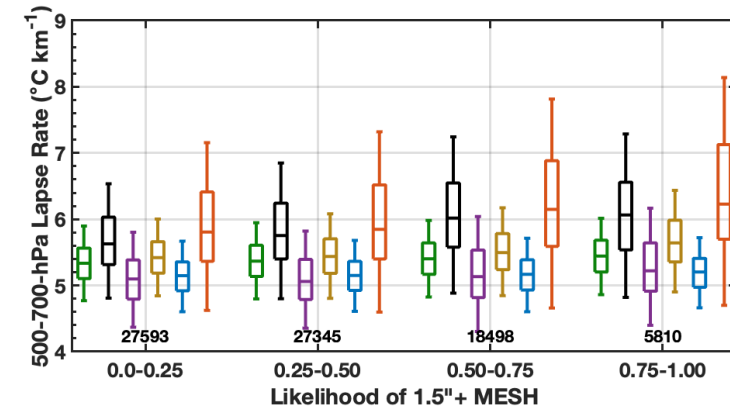
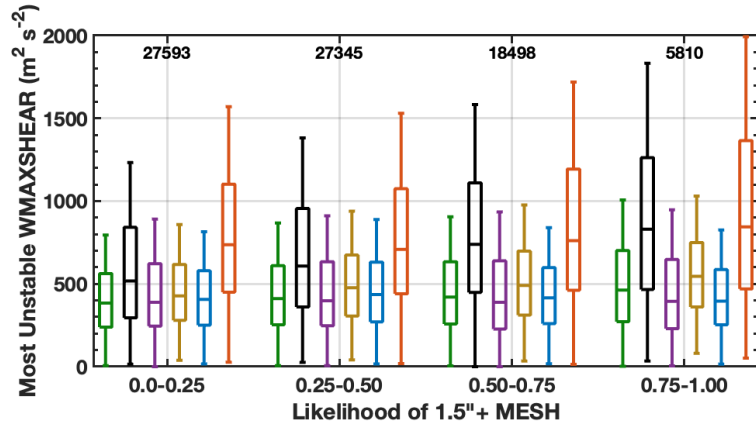


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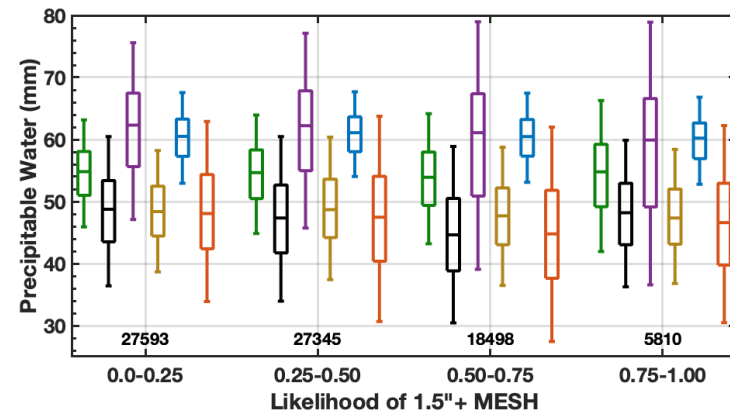
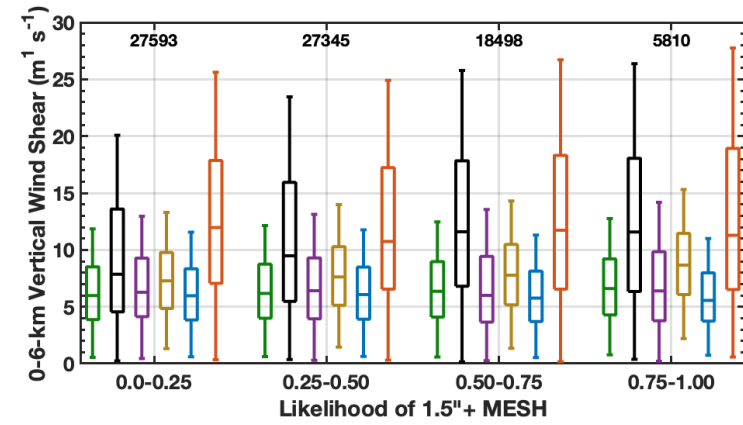


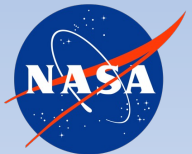


Additional Satellite MERRA2 by Region

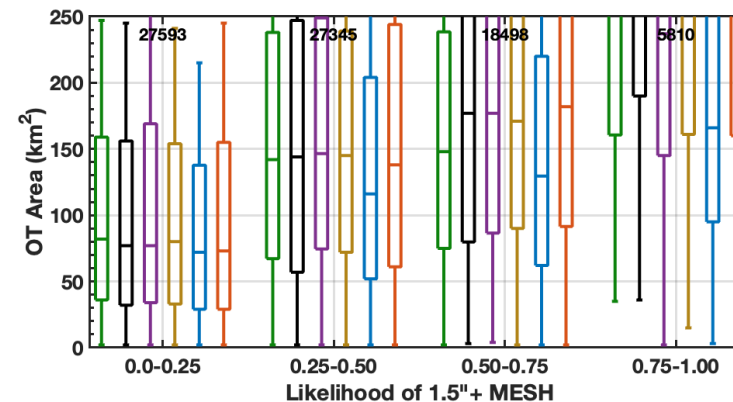
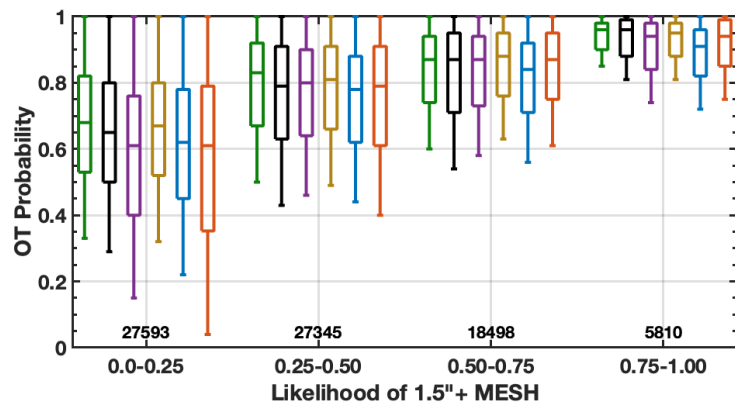


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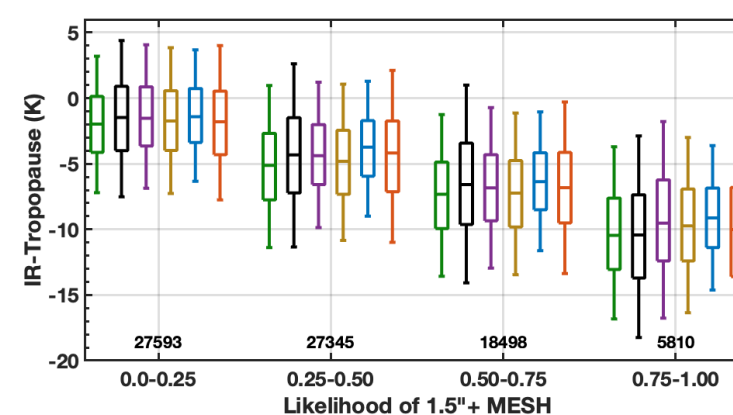
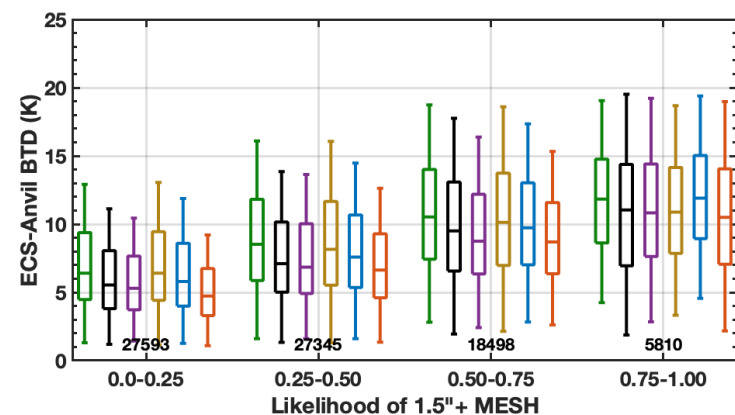




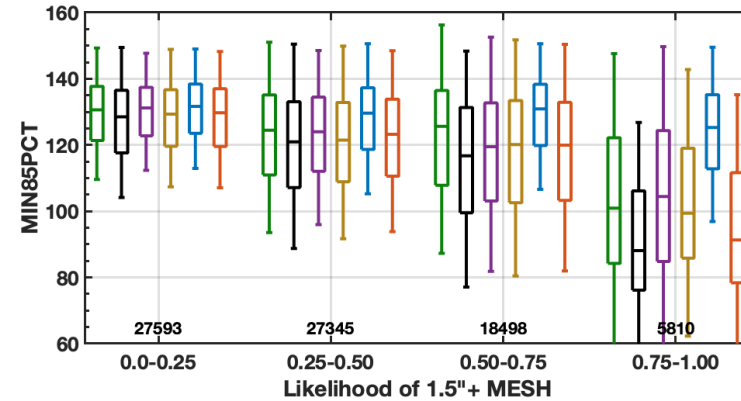
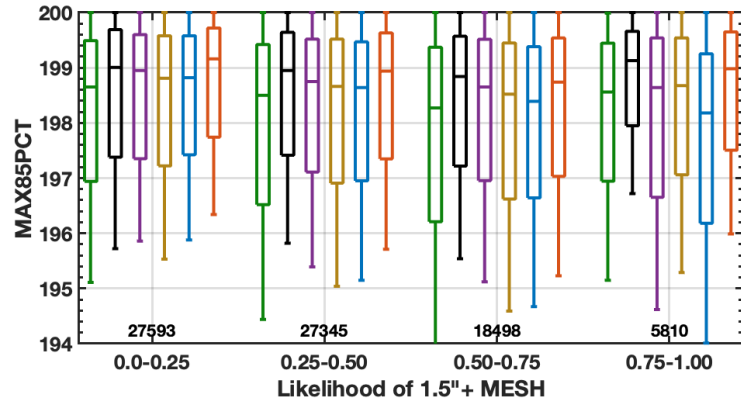
Additional Satellite IR by Region



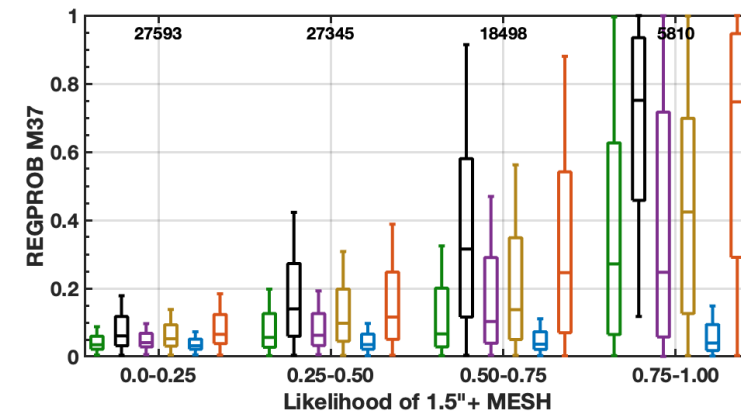
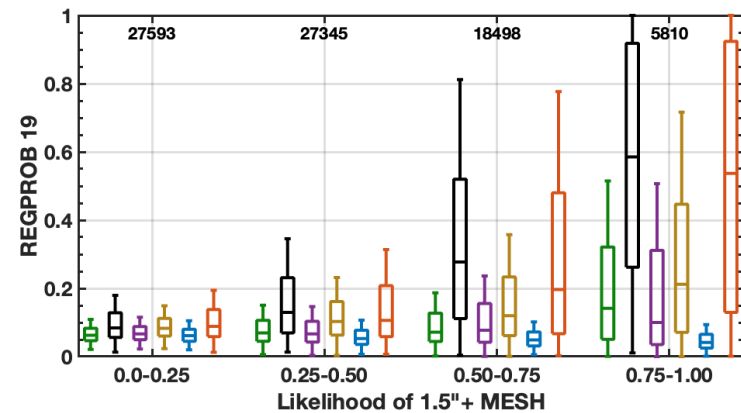
Amazon Argentina Bangladesh Tropical Africa Maritime Continent USA



Additional Satellite MWR by Region



— Amazon — Argentina — Bangladesh — Tropical Africa — Maritime Continent — USA



Additional Satellite MWR by Region

